On-the-Go Digital Soil Mapping for Precision Agriculture

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***Abstract*-The objectives of precision agriculture are to increase crop production profitability, improve product quality, and protect the environment. One of the first and most important areas in which precision agriculture has been applied is in managing the variability in soil properties, which is essential for the decision-making process. The success of precision agriculture depends strongly upon highly efficient and reliable methods for gathering and processing site-specific field information. The inability to obtain soil characteristics rapidly and inexpensively remains one of the biggest limitations of precision agriculture. "Predictive or digital" soil mapping is one of the hottest topics in soil science which demand of precision–agriculture for high-resolution spatial soil information. The objective of this article is to review current research into new mapping methodologies and assess whether they could be usefully applied with respect to precision agriculture. This paper determines the state of the art of predictive soil mapping, and discusses the potential of predictive soil mapping as part of an integrated management tool for precision agriculture. The various recent approaches and methods that have been, or could be, used for fitting quantitative relationships between soil properties or classes and their 'environment' are reviewed and discussed. To conclude the results, approaches to soil mapping can be divided into knowledge-based ones and data-driven ones. Conventional soil mapping has been criticized for being too qualitative. However, the pedometric methods have also been criticized for being too expensive as they require too many samples for them to be worthwhile. Of course the best features of these two may be combined into a mixed approach. Predictive soil mapping aims at spatial prediction of soil properties by combining soil observations at points with auxiliary information and remote sensing.**

Keywords- Precision Farming; Geostatistics; Pedometrics; Remote Sensing; Global Positioning System; Soil Mapping; Soil Properties

I. INTRODUCTION

Precision agriculture is "an integrated information- and production-based farming system that is designed to increase long term, site-specific and whole farm production efficiency, productivity and profitability while minimizing negative environmental impacts" [1, 2]. Precision agriculture aims to vary the inputs of agro-chemicals to individual fields to avoid over-application, which can lead to under-production, decreased profitability and adverse environmental effects [3]. For precision agriculture to be successful, three factors are required: (1) accurate site–specific data about field conditions [4], (2) an understanding of relationships between the data and economic/ environmental benefits, and (3) the ability to vary inputs by location.

To achieve these goals, a more detailed resolution of the variation in certain soil properties for site-specific application [5] and accurate maps of the soil properties are needed. There is a demand for accurate, highly efficient and reliable soil data to take decisive action in order to cope with the rising problems [2] and to ensure sustainable land use and management [6, 7]. However, soil data for present day applications are often required at resolutions unusual for classical soil surveys [8]. An important reason for the lack of quantitative spatial soil data is that conventional soil survey methods are slow and expensive [9]. The inability to obtain soil characteristics rapidly and inexpensively remains one of the biggest limitations for precision agriculture [10]. New methods for site-specific field information gathering and processing would be quite welcome.

One of the hottest topics in soil resource inventory is the pedometrics. Pedometrics is defined as: "the application of mathematical and statistical methods for the quantitative modelling of soils, with the purpose of analyzing its distribution, properties and behaviors". Pedometrics [11] refer to quantitative research in the field of pedology which would appear synonymous with predictive soil mapping (PSM). Pedometric mapping, predictive soil mapping [12], digital soil mapping [9] or concept mapping [13] is characterised as a quantitative, (geo-)statistical production of soil geoinformation. This offers possibilities to apply the developed techniques in precision agriculture where there is an urgent demand for accurate, quantitative soil data.

Several theoretical and applied aspects of the PSM have been discussed in the literature. To the best of author's knowledge, there has been no systematic analytical review of recent achievements of these studies for precision agriculture. The goal of this paper is to review and develop a method that can provide data for precision agriculture. To achieve this goal, the objectives of this review are to:

1- collect the latest published information on soil mapping in the context of precision agriculture and determine the state of the art of this subject;

2- identify the limitations and gaps in the current mapping approaches; and

3- suggest an accurate and inexpensive approach for soil mapping in the context of precision agriculture.

A literature review (from 1990 through 2009) to study the existing soil mapping methodology was carried out. The

articles were identified by searching all peer-reviewed articles in "ISI Web of Science", "SCOPUS" and "GEOBASE" using the search terms "digital soil mapping", "pedometric mapping", "predictive soil mapping", and "precision agriculture". The author reviewed each retrieved article's title, abstract, and keywords to ensure that it addressed soil mapping approach in the context of precision agriculture. These comprehensive reviews encompassed almost all important issues regarding mapping of soil properties and provided detailed information on the state of the art of this subject. Nevertheless, precision agriculture practitioners may find themselves not to be benefited from these reviews because they were more from a soil mapping perspective than from an agricultural perspective.

II. SURVEY THE CURRENT SOIL MAPPING LITERATURE FOR PRECISION AGRICULTURE

A. Knowledge-Based Soil Mapping Models

A variety of soil genesis models have been proposed in order to account for the high variability of soil and help further illustrate the difficulty of characterizing the soil landscape [14]. Three distinctive approaches have been employed: 1) factor models (e.g., [15]), where factors affecting soil development are identified; 2) process models (e.g., [16]), where soil-forming processes are emphasized; and 3) energy models (e.g., [17]), where the focus is upon process-driving mechanisms. In 1941, Jenny presented evidence that soils do not occur randomly on the landscape; rather, they are the product of specific soil-forming factors, known as the CLORPT model: climate, organisms, relief, parent material, and the time in which these act. This approach is dealing with the soil as a natural body. This means that soil characteristics co-vary in feature space. Different traditional soil mapping models are identified.

First, conventional (free) soil survey is based on the soil–landscape concept [18]. To map the soils, field soil mappers will first establish the soil–landscape model through field investigation. Free soil survey is the method which the mapper works mainly in the field [19] and is absolutely free in choice of location of auger bores and profile pits in order to systematically confirm a mental model of the soil-landscape relationships, draw boundaries, and determine map unit composition. Thus the surveyor's judgment and experience are very important. Some areas may have very few observations, if they fit exactly the mental model (i.e., the soil pattern can easily be predicted); other areas ('problem' areas) may be sampled in detail. The idea is that with the same sampling effort, a better map is made by concentrating on problem areas with scales 1:12 500 to 1:25 000. Of all the methods, it is the most commonly used method which is requiring the most effort in analysis and understanding of the milieu. The soil mappers then manually map the spatial extents of different soils or combinations of soils through photo interpretation (Fig. 1). It finishes in preparation of categorical maps. When applied to digital soil mapping, this model has concentrated on collecting digital data to represent each of the soil-forming factors, and then combining them according to expert judgment [20-22]. It simply uses the GIS to overlay existing data to predict soils, just as the pre-GIS mapper does intuitively. The difference is that the relations must be formalized.

Second, in grid mapping [19], the mapper dividing the zone to be mapped into small, similar areas (squares or rectangles) and then identifying in the field the soil present in each of these areas. This leads to making observations (profiles or auger) at the nodes of a regular net. Major limitations of grid mapping are the difficulty to defining the similarity between two soils [19]. Grid sampling, as a traditional way to explore in-field soil variation, has no longer been considered appropriate since it is labor intensive, time consuming and lacks spatial exhaustiveness.

Third, a variety of expert system approaches to PSM have been developed to utilize expert knowledge. The purpose of such methods is to exploit the information the soil surveyor accumulates while working in the field, by integrating such knowledge into the predictive model. The dependent variable in many expert systems models is often soil taxa or mapping unit. This apparent disadvantage of expert systems (using classification to characterize soil continuity) does make them easier to integrate into traditional soil survey. Expert systems differ from conventional models in two ways: (1) they store and manipulate qualitative information (allowing them access to information that cannot normally be used in other modelling frameworks); and (2) they are structured as meta-models (the knowledge is separated from the model) [23]. This allows the model to selectively choose which information is relevant at various stages of the modelling process, and it allows for information to be easily updated. Expert system development could be directly inserted into the traditional soil survey mapping approach as a substitute for the step where the surveyor converts his/her conceptual model into a choropleth map.

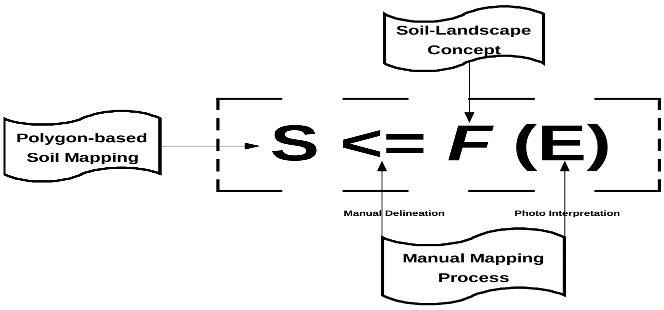

Fig. 1 Conventional soil mapping and its limiting factors [20]

B. Why Are Traditional Soil Mapping Not Suitable for Precision Agriculture?

In another question: what is wrong with conventional soil models for precision agriculture? Three criticisms have been identified in literature that causes of the low confidence in the soil mapping process. First, the operational quality of soil maps (i.e. accuracy, lineage and completeness) required is lower than expected [24] for precision agriculture. There is still a high chance that two soil surveyors, working

independently in the same pit, will identify two different types of soils. The final soil map has unknown assumptions, limitations and accuracy. Second, the soil boundaries are drawn by following the mental model in surveyor's head rather than by an objective procedure [25]. This results in an excessive dependence upon tacit knowledge and, as such, incomplete information exists relative to the derivation of the ultimate soil survey product [18]. Traditional soil mapping models fail to document most of the knowledge that the soil surveyor accumulates during the expensive field mapping process. In essence the soil survey is unfalsifiable and therefore untestable [26]. Hence, soil survey is still considered by some to be more of an art than a science [18]. Third, based on Fig. 1, the ability of soil scientists to conduct free soil surveys accurately and efficiently is largely limited by two major factors: 1) the polygon-based mapping practice; and 2) the manual map production process. The polygon-based mapping practice is based on the discrete conceptual model [27], which limits soil scientists' ability to produce accurate soil maps. Under this model, soils in the field are represented through the delineation of soil polygons with each polygon depicting the spatial extent of single-component mapping unit or a group of multiple-component mapping unit. A map unit is a collection of areas defined and named the same in terms of their soil components or miscellaneous areas or both. Each map unit differs in some respect from all others in a survey area and is uniquely identified on a soil map. Each individual area on the map is delineation (Table 1). The first problem associated with this polygon-based mapping practice is that it limits the size of the soil body which can be delineated as a polygon on a paper map. Soil bodies smaller than this size are either ignored or merged into the larger enclosing soil bodies.

TABLE I MAP SCALE AND MINIMUM DELINEATION SIZE

Intensity of Soil Survey	Map Scales for Field Mapping	Minimum Size Delineation, [Ha]
Syntheses	< 1 : 1,000,000	4030
Exploratory	1 : 250,000 to 1 : 1,000,000	252 to 4030
Low intensity	1 : 100,000 to 1 : 250,000	40.3 to 252
Medium intensity	1 : 25,000 to 1 : 100,000	2.52 to 40.3
High intensity	1: 10,000 to 1 : 25,000	0.40 to 2.52
Very high intensity	> 1 : 10,000	< 0.40

Existing data collection methods do not yield adequate soil information for precision agriculture in part because many of the processes that shape the soil landscape are still poorly understood. The complex and highly variable nature of soil patterns in landscapes complicates the labour-intensive process of collecting and presenting soil survey data [28]. The traditional methods do not yield quantifiable soil–landscape information that robustly describes actual soil variation. Traditional methods for defining soil distribution in landscapes are inadequate. There have been strong demands for quantitative information on finer and finer resolutions [29] for precision agriculture. So, there is a logical flow from these approaches into the new data-driven models.

C. Data-Driven Soil Mapping Model

The other approach for soil mapping is to look at the data, and develop (geo-)statistical models which can then be applied to predict soil properties at unsampled locations [29]. The Jenny CLORPT model has been extended to the so-called SCORPAN model, where the additional factors are **s**oil properties observed at a site or at nearby sites and neighbourhood, i.e. spatial position. The key point is that observations (factor 's') and their spatial positions (factor 'n') are explicitly incorporated into the model.

1) Geostatistical Approach: Concept, Theory, and Application:

Some of the fundamental problems facing both predictive soil mapping and precision agriculture specialists alike relate to issues of sampling, and of accurate classification and estimation. Geostatistics provides both the theory and the tools with which to address these problems. Geostatistics are a subset of traditional statistics that deal primarily with spatial data and account for spatial autocorrelation using kriging as the spatial interpolator. The concept is based upon the theory of regionalized variables, which was mainly developed by [30] and [31]. The geostatistical method of spatial interpolation is termed kriging. Kriging is a generic name for a family of generalized least-squares regression algorithms. Kriging is a form of weighted local averaging that uses a measure of spatial dependence, the variogram, to determine the weights applied to the data when computing the averages. From the variogram one may: estimate summary statistics such as the dispersion or sample variance; estimate regularized variograms for new spatial resolutions; estimate optimally at unsampled locations from sample data; design optimal sampling strategies before the actual survey; and conditionally simulate at unsampled locations from sample data.

The application of geostatistics in soil science ensures a quantitative description of the spatial variation of soils, improves accuracy in the estimation of soil properties [32]. The main application of geostatistics to PSM and precision agriculture has been the estimation and mapping of soil attributes in unsampled areas. An important contribution of geostatistics is the assessment of the uncertainty about unsampled values, which usually takes the form of a map of the probability of exceeding critical values for soil quality [33]. Geostatistical approaches use sampled and analyzed data to interpolate soil-attribute maps [34]. Geostatistical methods have been used in soil mapping for precision agriculture research to spatially interpolate soil property values at unmeasured sites from field-collected data.

Table 2 compared the various modelling methods. Ordinary Kriging (OK) provides the "best" optimal and unbiased linear technique for estimation of unknown values from sample data. The estimate is obtained by weighting each of several sample data that are proximate to the estimate. OK has played a major role in predicting the soil variable and maps of soil properties [35-40]. OK has been used in soil reclamation, soil classification (e.g., [41, 42]), soil salinity and fertility studies [43, 44] and soil pollution studies (e.g., [45-47]). In order to accommodate a trend

within a dependent soil variable universal kriging has been used [11]. Block kriging involves determining estimates over meaningful areas rather than at specific points [48]. Kriging with external drift is similar to universal kriging, but it uses an ancillary variable to represent the trend [29]. Co-kriging is simply the extension of kriging to more than one variable. It is most likely to be beneficial where the primary variable (that to be estimated) is undersampled with respect to the secondary variable(s). This is clearly the case in remote sensing where the secondary variable is provided by remotely sensed imagery which often completely covers the scene of interest. Co-kriging takes advantage of correlation that may exist between the variable of interest and other more easily measured variables [49]. Regression kriging, hybrid interpolation techniques [50], involves spatially interpolating the residuals from a non-spatial model by kriging, and adding the result to the prediction obtained from that model [51, 52]. Factorial kriging is another method to integrate multivariate data into the standard kriging routine to extrapolate soil data [53].

TABLE II MODELLING METHOD, DEPENDENT, AND ENVIRONMENTAL VARIABLES USED IN THE PREDICTIVE SOIL MAPPING MODELS

Authors	Predictive Factors (SCORPAN)	Dependent Variables (S)	Predictive Model (F)	Environmental Variables	No. of Observations	Predicted Soil Class
[54]	ND	Clay content	Kriging, cubic spline	None	ND	ND
[48]	ND	Clay content	Block kriging	None	ND	ND
[55]	s, o, r	Soil landscape unit	Expert/ bayesian expert system	Veg. type, wetness index, gradient, terrain position	53	Soil unit
[53]	ND	Total carbon, pH, N, CEC, K, Ca, Mg	Factorial kriging	None	ND	ND
[56]	ND	Fuzzy classes	Fuzzy-k-means with extragrades	Field collected physical chemical and morphological soil properties	ND	ND
[41]	ND	Fuzzy classes	Fuzzy-c-means and kriging	Field-collected physical chemical and morphological soil properties	ND	ND
[57]	ND	Clay, CEC, pH, EC, bulk density, θ at -10 and -1500 kpa	Generalized linear models (logit)	Slope, relief, landform, slope position	ND	ND
[58]	ND	A horizon depth, OM and P content, pH, silt and sand	Linear regression	Slope, wetness and stream power indices, aspect, curvature	ND	ND
[49, 59]	r, n	Solum depth, depth to bedrock, gravel and clay content, OM	Linear regression, kriging, co- kriging, regression kriging	Slope, aspect, curvature	194	Soil series
[60]	ND	A horizon and solum depth, E horizon presence	Linear and logit regression	Curvature, CTI, topo. position	60	Soil series
[61]	s, n	Soft layer depth	Kriging, co-kriging, regression kriging	Hillslope position	539, 117	Soil series
[25]	ND	OM	Baysian rule-based methods	Slope, aspect, wetness index	ND	ND
[62]	ND	Soil erosion class	Decision tree analysis, neural networks	Slope, aspect, wetness index, flow length and accumulation, Landsat TM, tree cover	ND	ND
[63]	ND	Field and laboratory collected physical, chemical and morphological soil properties	A large variety of statistic methods	A variety of digital environmental data	ND	ND
[27, 64]	ND	Soil series, A horizon depth, individual series maps	Fuzzy logic expert system (SoLIM)	Elev., aspect, canopy coverage, gradient, curvature	ND	ND
[65]	ND	Drainage class	Classification tree	Elev., aspect, NDVI	ND	ND
[66]	ND	Solum depth, P and N content	Regression tree and linear regression	Elevation, slope, curvature, CTI, contributing area, downslope means for slope, climate data, Prescott Index, Gamma Radiometry, Landsat TM	ND	ND
[67]	s, o, r	OC	Linear and exponential regression	Slope, curvature, aspect hillslope position	745	Soil classes
[52]		CEC, pH, N, P, K, Na	Factorial kriging	None explicitly used	ND	ND
[68]	r, n	Thickness of horizon	Kriging with external drift	ND	219	Soil classes
[69]	r, n	Hydromorphic index	Kriging, co- Kriging	ND	182	Soil classes
[70]	o, r	ND	GLM (discriminant analysis)	ND	1236	Soil classes
[71]	c, r, p	Clay content, CEC	GLM, GAM, regression trees, neural networks, kriging, co-kriging, regression kriging	ND	2800	Soil classes

TABLE II (CONTINUED) MODELLING METHOD, DEPENDENT, AND ENVIRONMENTAL VARIABLES USED IN THE PREDICTIVE SOIL MAPPING MODELS

Authors	**Predictive Factors (SCORPAN)**	**Dependent Variables (S)**	**Predictive Model (F)**	**Environmental Variables**	**No. of Observations**	**Predicted Soil Class**
[72]	r, p	ND	Discriminant analysis	ND	1000	Soil unit
[73]	p	OC, N_2O	Land form segmentation	ND	25	Soil unit
[74]	c	ND	Fuzzy classification	ND	600	Soil classes
[75]	p	Hydromorphic index	Logistic Regression	ND	141+41+54+ 162+308	Soil classes
[76]	r	Soil moisture, residual P, solum thickness, depth to $CaCO_3$, OC	Linear regression	ND	210	Soil classes
[77]	c, o, r	pH, OM	Linear regression	ND	2350	Soil classes
[78]	s, o, r	Silt, CEC, Mn	ANN, regression tree, GLM	ND	502	Soil classes
[79]	s, o, r, p	Available water capacity	Rule-based	ND		Soil classes
[46]		Heavy metal	Ordinary kriging	ND	223	Probability map
[50]	r	Topsoil thickness, pH, OM	GLM, regression kriging	ND	135	Soil classes
[36]	ND	EC	Ordinary kriging and Bayesian maximum entropy	ND	413	Soil classes
[37]	ND	Texture, OM, pH, phosphorus and potassium	Ordinary kriging, ordinary kriging plus regression	Aerial color photograph	86	Soil maps
[80]	ND	Pb contamination	Ordinary kriging, ordinary kriging with robust estimation of the variogram and lognormal kriging	ND	72	Probability map
[81]	ND	CEC, PH, OC and clay content	Ordinary kriging, universal kriging and regression kriging	Ecological zone, Soil type, geology,	147	Soil classes
[38]	ND	EC	Ordinary kriging, and regression kriging	Spot image, vegetation index	547	Salinity map
[82]	ND	pH	Ordinary kriging, simple kriging, and indicator kriging	ND	165	Probability map
[83]	ND	EC, N, P, K, pH and saturated soil hydraulic conductivity	Ordinary kriging	ND	25	capability map
[84]	ND	Heavy metals Cu, Zn, Pb, Cr and Cd.	Ordinary kriging, lognormal kriging, and Cokriging	ND	450	Soil classes
[85]	ND	Texture	Regression kriging	MODIS satellite images	450	Soil classes
[86]	ND	EC, OM, CEC and total nitrogen	Ordinary kriging	SPOT image and vegetation index	139	ND
[87]	ND	Copper	Ordinary kriging, simple and Co-kriging	ND	2202	Soil classes
[88]	ND	pH, Zn, cly content and total nitrogen	kriging with external drift, cokriging and regression kriging	Satellite image	ND	ND
[89]	ND	Total phosphorus	Regression Kriging and Co-kriging	Landsat ETM+ and ASTER images	111	Soil classes
[39]	ND	EC	Cokriging and Regression kriging	ND	240	Soil clases
[47]	ND	pH, OC, iron oxides and total content of As, Cu, Cr, Hg, Pb, Sb, U, Zn, Mn, S, Fe Al, Ca, K, Mg and P	Ordinary kriging, cokriging and indicator kriging	Hyperspectral image	90	Soil clases
[40]	ND	Total carbon, total nitrogen and sand, silt, clay content	Simple kriging, ordinary kriging and regression kriging	DEM, NDVI and remote sensing data	212	Soil map

2) Auxiliary Information:

Table 3 shows three types of soil auxiliary information ('predictors') for PSM and precision agriculture: Remote sensing, Terrain parameters, and Thematic maps.

2.1 Remote Sensing Data and their Applications to Precision Agriculture:

Remote sensing data are an important component of precision agriculture and PSM because they provide a spatially contiguous, quantitative measure of surface reflectance, which is related to some soil properties [91]. Both physical factors (e.g., particle size and surface roughness) and chemical factors (e.g., surface mineralogy, organic matter and moisture) control soil spectral reflectance [92]. Table 4 presents a range of optical remote sensing instruments that provides data suitable for use in precision agriculture. Selection of the most appropriate data source depends on the temporal, spectral and spatial characteristics of the predictive soil mapping need.

TABLE III REMOTE SENSING, TERRAIN PARAMETERS AND THEMATIC DATA FOR SOIL INVENTORY

Data Type		**Detailed Resolutions < 20 m**	**Medium Resolutions 20 – 200 m**	**Coarse Resolutions > 200 m**
Remote Sensing Imagery	Multi-spectral imagery	IKONOS, SPOT	LANDSAT, ASTER	MODIS, MERIS
	Hyper- spectral imagery	-	AVIRIS	AVHRR
	Radar and radiometerics imagery	Airborn EM, LIDAR	-	ASAR, MWR
Terrain parameters	Topographic information	National Mapping Agencies	SRTM	GTOPO
Thematic maps	Climatic variables	-	National Meteorological Agencies	MARS
	Vegetation / land cover maps	-	-	-
	Geological and parent material maps	-	Geological Survey	FOREGS
	Soil delineations	Regional soil survey	National Soil Survey	ESBN

Source [90]

TABLE IV CHARACTERISTICS OF OPTICAL SENSORS FOR PRECISION AGRICULTURE AND PSM

	Temporal Resolution			**Spatial Resolution**			**Spectral Resolution**		
	On demand	**1-10 days**	**10+ days**	**< 5 m**	**5-20 m**	**> 20 m**	**Visible-NIR**	**SWIR**	**TIR**
Landsat TM			+			+	+	+	+
Landsat ETM+			+		+	+	+	+	+
Spot I-IV		+			+		+		
Spot V		+		+	+		+		
IRS-IC		+			+	+	+	+	
IRS-ID		+			+	+	+	+	
ASTER			+		+	+	+	+	+
Quickbird		+		+	+		+		
IKONOS		+		+	+		+		
Aerial Photography	+			+			+		
Airborne Scanning	+			+			+	+	+
Laser Scanning	+			+					

Table 5 provides a slightly more detailed overview with five resolutions of interest. The third one (D3) which deals with sub catchments, catchments and regions is the one which attracts the most attention. In the language of digital soil maps [93], different from that of conventional cartography, scale is a difficult concept, and is better replaced by resolution and spacing. D3 surveys, which in conventional terms, have a scale of 1:20,000 down to 1:200,000, have a block or cell size from 20 to 200 m, a spacing also of 20–200 m and a nominal spatial resolution of 40–400 m (Table 5). This order was suggested for applications in precision agriculture.

Table 6 is summarized types of sensors that have been used for soil studies. Majority employed high spatial resolution sensors, the Landsat TM with 30 meter, the SPOT with 20 meter resolutions and IRS LISS II with 23 meter resolution. The thermal band of the Landsat TM has shown to be significant in contributing to the separability of soil categories through its ability to characterize the clay, organic matter, and iron-oxide content of the soil.

Recent developments in hyperspectral remote sensing offer the potential of improving data input to predictive soil models and for precision agriculture. Hyperspectral sensors,

such as the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) measure a contiguous spectrum in the visible and NIR, and thereby better characterize atmospheric and surface properties [94]. The large number of spectral bands permits direct identification of minerals in surface soils. Hyperspectral sensors have been found to be useful in mapping mineralogical features such as iron oxides [95], carbonates and sulphates [96]. Clark and Swayze [97] mapped over 30 minerals using AVIRIS. Palacios-Orueta and Ustin [98] showed that enhanced spectral information was suitable for discriminating even subtle spectral changes associated with differences in organic matter and iron content. Other examples of the application of AVIRIS to aid soil mapping include [99-101].

Sensors that operate in the microwave portion of the electromagnetic spectrum have also shown promise in soil mapping and precision agricultural research. Active radar systems can be designed to collect data which can be used to produce high resolution and extremely accurate DEMs (e.g., [102]). Synthetic aperature radar (SAR) is one example of an active system.

TABLE V SUGGESTED RESOLUTIONS AND EXTENTS OF DIGITAL SOIL MAPS

Name*	USDA Survey Order	Pixel Size And Spacing	Cartographic Scale	Nominal Spatial Resolution
D1	0e	< (5x5) m	>1:5000	< (10x10) m
D2	1, 2	(5x5) to (20x20) m	1:5000 – 1:20,000	(10x10) to (40x40) m
D3	3, 4	(20x20) to (200x200) m	1:20,000 – 1:200,000	(40x40) to (400x400) m
D4	5	(200x200) to (2x2) km	1:200,000 – 1:2,000,000	(400x400) to (4x4) km
D5	5	>(2x2) km	< 1:2,000,000	>(4x4) km

* This order was suggested by Pierre C. Robert, University of Minnesota, for applications in precision agriculture. This table adopted from [29].

SAR has been used to aid soil property mapping, such as soil salinity [103] and soil moisture [104, 105]. Active remote sensing, like radar sensing has been successfully used for surface structure measurement, and also for measuring direct soil properties like surface roughness and soil moisture contents. Information can be obtained by radar which can penetrate through soil to a depth that is equal to 10 – 25 % of their wavelength if there is a light-textured soil (low dielectric constant) over a heavier textured horizon (high dielectric) or a water table (very high dielectric) [106].

TABLE VI EXAMPLES OF SOURCES OF EXOGENOUS DATA FOR SOIL INVENTORY AND PRECISION AGRICULTURE

Carrier	Sensor/Scanner	Land/Soil Information
Air-borne: (Aeroplanes and Balloons)	Photogrammetric/videographic cameras SLAR NIR Gamma-radiometer	DEM, crop growth, vegetation Moisture, landscape Moisture, clay, etc. K, U and Th isotopes
Space-borne: Landsat	Multi-spectral thematic mapper, etc	Vegetation, moisture
SPOT Satellites	High resolution visible (panchromatic and multispectral)	DEM, landscape, vegetation and moisture
NOAA Satellites	Advanced very high resolution radiometers (AVHRR)	Soil, vegetation, moisture (drought)
Proximal Sensors and Scanners	Time domain reflectrometer (TDR) Electromagnetic induction (EM) Gamma-radiometer Soil chemical sensors Yield monitors Soil compaction	Moisture Salinity, clay and moisture K, U and Th isotopes Soil fertility, organic carbon, etc Yield data associated with soil variability Soil resistance

Developments in ground-based sensors show the promise to provide data sources complimentary to image-based information when trying to develop detailed soil property maps. Proximal sensing offers the possibility of producing high resolution maps of soil properties (D1 mapping, Table 5).

Precision agriculture utilizes electronic information technologies to modify land management in a site-specific manner as conditions change spatially and temporally. The fundamental components of precision agriculture include commercialized technologies of GPS, yield-monitoring, and variable rate agrichemical application combined with adaptation of existing technologies of GIS and remote sensing (e.g., electromagnetic induction, aerial photography, satellite- and airborne multispectral imagery, microwave, and hyperspectral imagery).

Global Positioning System (GPS) receivers, used to locate and navigate agricultural vehicles within a field, have become the most common sensors in precision agriculture. In addition to having the capability to determine geographic coordinates (latitude and longitude), high accuracy GPS receivers allow measurement of altitude (elevation) and the data can be used to calculate slope, aspect and other parameters relevant to the terrain. When a GPS receiver and a data logger are used to record the position of each soil sample or measurement, a map can be generated and processed along with other layers of spatially variable information. This method is frequently called a “map-based” approach.

Fig. 2 shows the classification of soil variability using on-the-go soil sensing technology. The major benefit of on-

the-go sensing and vehicle-based soil sensors has been the ability to quantify the heterogeneity (non-uniformity) of soil within a field and to adjust other data collection and field management strategies accordingly. Most on-the-go soil sensors for measuring soil properties being developed involve one of the following measurement methods (Fig. 2): 1) electrical and electro-magnetic sensors that measure electrical resistivity/ conductivity or capacitance affected by the composition of the soil tested, 2) optical and radiometric sensors that use electromagnetic waves to detect the level of energy absorbed/reflected by soil particles, 3) mechanical sensors that measure forces resulting from a tool engaged with the soil, 4) acoustic sensors that quantify the sound produced by a tool interacting with the soil, 5) Pneumatic sensors that assess the ability to inject air into the soil, and 6) electrochemical sensors that use ion-selective membranes producing a voltage output in response to the activity of selected ions (e.g., hydrogen [H], potassium [K], nitrate [NO_3^-], etc.).

Electromagnetic induction (e.g., EM38-MK2, EM31-MK2, EM-34-3, EM63, and GEM300 sensors) uses electromagnetic energy to measure and map spatial and temporal variations in the soil. Electromagnetic induction (EMI) is a relatively low-cost and rapid method for measuring, assessing spatially soil properties. Soil bulk electrical conductivity (soil electric resistivity) reflects a combination of soil mineralogy, salts, moisture and texture; hence, it is a good compound measure of soil.

Optical and radiometric sensors use light reflectance or another electromagnetic wave signal (Ground Penetrating Radar - GPR) to characterize soil. GPR provides quantitative measurement for use in pedometrics [107, 108]. GPR detects buried objects by emitting radio waves into the ground and then analyzing the return signals generated by wave's reflections at the boundaries of materials with different indexes of refraction caused by differences in electrical properties. Several researchers have correlated soil reflectance with soil chemical properties…i.e., soil NO_3^- or phosphorus (P) content and pH. Some researchers are utilizing GPR to investigate wave movement through the soil. Changes in wave reflections may indicate changes in soil density or restricting soil layers. Ground penetrating radar has great potential for agriculture especially to support water management. Also, these sensors measure near-infrared, mid-infrared, or polarized light reflectance. Internal detectors include, for example, the neutron probe and time domain reflectometry (TDR), both providing an estimate of soil moisture. The soil can be analyzed from an external, or remote position, and gamma radiometric.

The mechanical sensors can be used to estimate soil mechanical resistance (compaction). These sensors use a mechanism that penetrates or cuts through the soil and records the force measured by gauges or load cells. Acoustic and pneumatic sensors serve as alternatives to mechanical sensors when studying the interaction between the soil and an agricultural implement. Pneumatic sensors were used to measure soil air permeability on-the-go.

Finally, electrochemical sensors can provide the most important type of information needed for precision agriculture-soil nutrient availability and pH. When soil samples are sent to a soil-testing laboratory, a set of recommended laboratory procedures is performed.

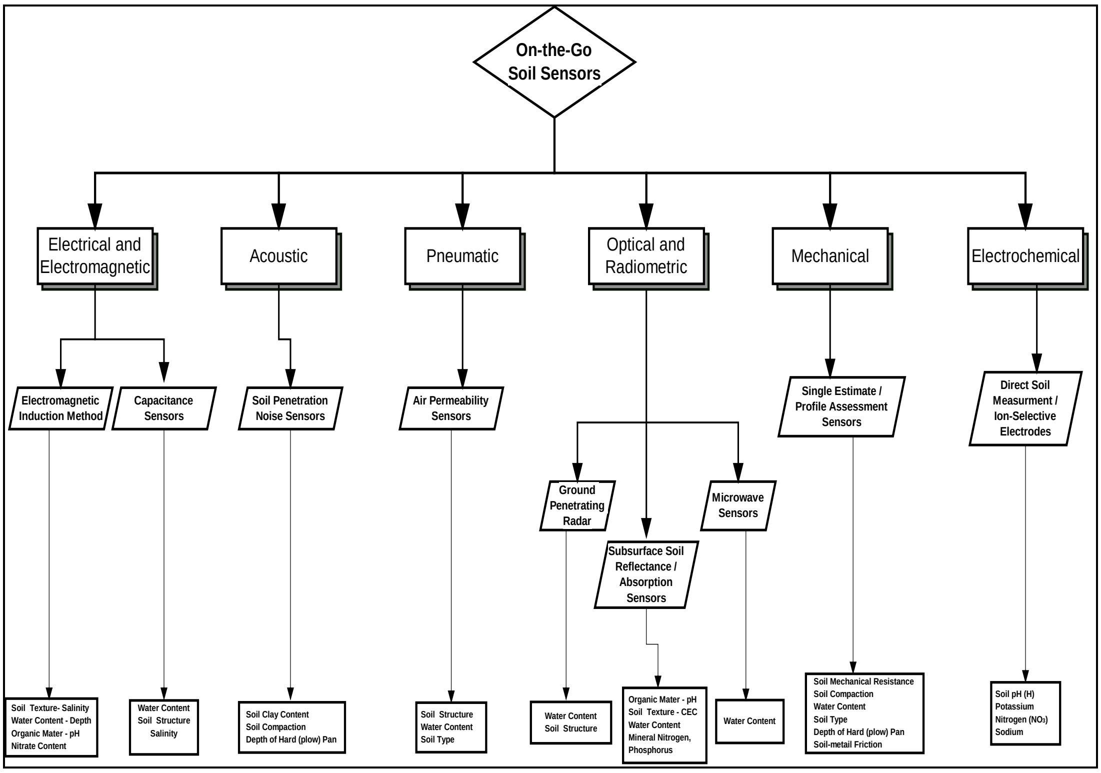

Fig. 2 Characterizing and classification of soil variability using on-the-go soil sensing technology

(Adopted from V.I. Adamchuk, SSMG-44, www.ppi-far.org/ssmg.)

These procedures involve sample preparation and measurement. Some measurements (especially pH determination) are conducted using an ion-selective electrode, or an ion selective field effect transistor. These electrodes detect the activity of specific ions (NO_3^-, K, or H in the case of pH).

All these instruments have been used extensively in precision agriculture for mapping soil types and properties [10, 109-111]. Although various on-the-go soil sensors are under development, only the electrical and electromagnetic sensors have been widely used in precision agriculture. Soil sensors may be useful in identifying areas within fields which are less profitable or environmentally risky to farm.

Improved soil discrimination might be afforded by estimates of biomass variation within particular land uses. This estimation has been developed using visible and near-infrared vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) for natural vegetation and for crops [112]. Improved estimation can be obtained by hyperspectral imagery in the visible-NIR range [113] or through the use of microwave imagery [114]. The use of yield monitors on harvesting machines also provides a source of spatial biomass information [115]. Bishop and McBratney [109] used yield-monitored wheat yield to aid in the prediction of soil clay content. Yield-monitored data are currently useful for D1 mapping for precision agriculture.

Table 7 shows summaries of information reported for remote sensing of precision agriculture and PSM on soil chemical, physical, and other soil properties. Nearly 90 % of the studies reported using wavelengths at the visible (VIS) and near-infrared (NIR) regions of the electromagnetic spectrum. Most of the fundamental spectral signatures of soil components occurred in the mid-infrared (MIR) to thermal-infrared regions. However, combinations of fundamental features and their overtones cause strong and distinct spectral signatures in the VIS and NIR regions. This fact makes the VIS-NIR regions very informational and diagnostic for many soil components.

Besides mapping soil classification categories, physical and chemical soil characteristics are often estimated with RS data. Some soil properties are directly related to the surface color and thus relatively easy to map when the soil is bare and visible spectra is used to detect the color.

Iron-oxide and OM content, and partly the soil moisture contents and soil texture are good examples of that. Other soil features, like many of the chemical properties of the deeper horizons, can be detected only indirectly, through the type and the condition of the surface vegetation. These relationships are often indirect and explain less of the total spatial variation than the one for the soil surface properties. As can be seen in Table 7, soil properties which were frequently investigated by different researchers include textures (clay, silt, sand), organic matter (OM), pH, salt, iron-oxide content, nutrients [nitrogen, phosphorous (P), potassium (K), calcium (Ca), magnesium (Mg), Zinc (Zn), sodium (Na)], hydrological properties [electrical conductivity (EC), moisture content (MC), and cation exchange capacity (CEC)]. These soil properties are believed to have great impacts on crop growth and hence precision agriculture. It can also be seen that soil properties studied by different authors varied greatly and the variation is strongly dependent upon the geographic regions where the studies were conducted.

Regardless of the type of system, remote sensing data and derived products are potentially useful explanatory variables in predictive soil mapping models for precision agriculture.

2.2 Terrain Parameters and Soil Properties for Precision Agriculture:

Methods used to derive terrain attributes have been greatly refined over the last 15 years. Future satellites aiding in the development of more accurate digital elevation models (DEM) will make terrain analysis an increasingly important component of predictive soils mapping [58, 116]. Several review articles have been devoted to the role of terrain analysis in soil mapping [117, 118]. Relief or landform shape can be characterized with the use of (DEM). The terrain can also reflect indirectly part of the effects of the other four soil forming factors. Shary et al. [119] defined 12 types of curvature that potentially can be used for landform classification and spatial prediction. The most commonly used DEM derived terrain variables are shown in Table 8.

Relief or topography can be characterized with the use of digital elevation models (DEM). DEM is used to derive quantitative measures of soil forming processes, also called terrain parameterization. This is a process of quantitative description of terrain by terrain parameters. These can be derived using various algorithms that quantify morphological, hydrological, ecological and other aspects of a terrain. Extracted terrain parameters can then be used, for example, to improve mapping and modelling of soils for precision agriculture, vegetation, land use, geomorphologic and geological features. It is relatively simple and easy to derive the primary features of terrain parameters (e.g. slope, gradient, aspect, curvature). The secondary features of terrain parameters describe more complex characteristics of the landform, which are linked to certain terrain-regulated processes, like stream power index or the compound topographic index (CTI). These features can be used to estimate potential soil loss. Also it used for calculating climatic variables, like temperature, solar irradiation, long wave surface radiation, reflected radiation, which are important factors in the energy balance of the surface and thus in the soil formation. Many successful applications of DEM and DEM-derived data have been made in large and medium scale mapping. Table 9 summarizes those studies used digital terrain information for soil characterization.

2.3 Thematic Mapping:

There are four major groups of the thematic data: climate, organism, relief, parent material and time. McBratney et al. [9] added the geographical location of the soil profiles and the available soil properties that show correlation with the ones to be estimated. These are the major inputs of a statistical framework (SCORPAN) used to predict soil

variables at each location of the study of interest. A common spatial prediction technique that can be used to apply SCORPAN model is the regression-kriging. Regression-kriging is used to estimate the unknown soil parameters. These models assume that there is a stochastic relationship between various predictors and target soil variables, although it can also be used to improve the deterministic models of soil genesis [85].

3) Statistical Models:

Statistical methods can be used to exploit the relationship between quantifiable landscape indices and soil properties to create predictive soil maps. Statistical methods do demonstrate in a quantitative manner that terrain analysis can be used to predict soil attributes in relatively small areas with homogeneous parent material. For example, [57] used a regression to account for a large percentage of variation for many soil characteristics (A horizon: clay content, CEC, EC, pH, bulk density; B horizon: clay content, CEC, ESP, EC, pH, bulk density) using a variety of predictor variables (slope, presence or absence of impeding layer, relief, landform, topographic position). Linear regression has also been used with terrain variables derived from a 15-m DEM to predict soil attributes (organic matter content, extractable phosphorous, pH and texture) at unvisited sites [58]. In that particular study, 50% of the variance of A-horizon thickness was explained by slope and the wetness index.

TABLE VII SUMMARY OF INFORMATION REPORTED FOR REMOTE SENSING OF PRECISION AGRICULTURE ON SOIL CHEMICAL AND PHYSICAL PROPERTIES

Author	Sensing Technique						Soil Properties																				
	UV	VIS	NIR	MIR	TH	MW	N	P	K	Ca	Mg	Na	Zn	OM	EC	CEC	pH	Sand	Silt	Clay	MC	Others
[91]		+	+																			
[120]		+	+	+	+									+				+	+	+		Total C
[121]			+				+															Total C
[122]														+		+		+		+		Ca CO_3, Fe
[123]		+	+	+	+																	
[124]			+											+		+				+	+	
[125]		+	+																			
[126]			+											+		+				+		Ca CO_3
[127]		+	+											+							+	
[128]	+	+	+																			
[99]	+	+	+											+				+	+	+		
[129]		+	+					+	+	+	+	+			+		+					S, Mn, Fe
[130]		+	+															+	+	+		
[131]			+				+	+	+	+	+	+	+			+	+	+	+	+	+	
[132]							+								+	+	+	+	+	+		
[133]		+	+					+	+	+	+	+	+				+		+	+		
[1]														+							+	
[134]		+	+						+	+	+							+	+	+		Mn, Fe
[135]		+	+					+	+	+	+			+			+	+	+	+		
[136]								+														
[137]	+	+	+					+	+	+	+			+	+		+					
[138]		+	+				+	+	+	+	+		+				+				+	
[139]		+	+					+	+	+	+	+	+						+	+		
[140]		+	+																	+		
[141]		+	+											+								
[142]		+	+																		+	
[143]		+	+	+	+			+														Cu
[144]		+	+											+								

UV= ultraviolets, VIS= visible, NIR= near infrared, MIR= mid infrared, TH= thermal infrared, MW= microwave

TABLE VIII SUMMARIES OF THE MOST TERRAIN FEATURES USED FOR SOIL MAPPING AND PRECISION AGRICULTURE

Topographic Variable (Unit)	**Definition and Formula / Landscape Characteristics**
Elevation (m)	Elevation above sea level at a given point on the land surface. The vertical zonality of vegetation and soils in mountainous regions. An indicator of the rock's stability to weathering
Gradient (degree)	An angle between a tangent and a horizontal plane at a given point on the land surface: $G = \arctan\sqrt{p2 + q2}$ Flow velocity, runof and soil loss, thickness of soil horizons, some plant characteristics.
Aspect (degree)	An angle clockwise from north to a projection of an external normal vector to a horizontal plane at a given point on the land surface: $A = \arctan(q / p)$ Flow direction, thickness of soil horizons, some plant properties.
Profle curvature (m^{-1})	A curvature of a normal section of the land surface by a plane, including a gravity acceleration vector at a given point: $kv = -\frac{p2r + 2pqs + q2t}{(p2 + q2)\sqrt{(1 + p2 + q2)3}}$ Relative deceleration of flows, soil moisture, pH, thickness of soil horizons, organic matter [145, 146], plant cover distribution [147]. An indicator of lineaments, ring structures [148] and fault morphology [149].
Plan curvature (m^{-1})	A curvature of a normal section of the land surface. This section is orthogonal to the section of profile curvature at a given point on the land surface: $kh = -\frac{p2r + 2pqs + q2t}{(p2 + q2)\sqrt{1 + p2 + q2}}$
Mean curvature (m^{-1})	H = (kh+Kv)/2, where kh and kv are plan and profile curvatures, respectively. Flow convergence and relative deceleration with equal weights [150], soil moisture [151], plant cover distribution [147].
Slope length (m)	The distance from a point of flow origin to a point where either gradient decreases enough that deposition begins or flows enters a channel. A soil loss.
Relief (m)	RFi = hmax – hi, where hmax is the highest elevation in a study site and, hi is the elevation value at a given point on the land surface. Landscape drainage characteristic
Topographic factor	A ratio of soil loss per unit area from a slope to that from a 22.15 m length of uniform 9% slope under otherwise equal conditions: LS = (L/22.15)m (6541 sin 2 S + 4.56 sin S + 0.065) Where L is slope length, S is a gradient (%) and m = 0.2 – 0.5 depending on gradient. A soil loss.
Topographic index	TI = ln (CA/G), where CA and G are the specific catchment area and gradient, respectively. Flow accumulation, soil moisture, distribution of saturation zones, depth of water table, evapotranspiration [152], thickness of soil horizons, organic matter, pH, silt and sand content [58] , plant cover distribution [147]
Stream power index	SI = CA . G, where CA and G are the specific catchment area and gradient, respectively [145]. Potential erosive power of overland flows [145] , thickness of soil horizons, organic matter, pH, silt and sand content [58], plant cover distribution [147]
Reflectance (the Lambertian model)	$R = \frac{1 - p\cos\theta / \tan\psi - q\sin\theta / \tan\psi}{\sqrt{1 + p2 + q2}\sqrt{1 + (\cos\theta / \tan\psi)2 + (\sin\theta / \tan\psi)2}}$ where y and c are the solar azimuth and zenith angles, respectively

r, t, s, p and q are partial derivatives of the function Moving the 3 * 3 elevation submatrix along a regular DEM, we can calculate values for r, t, s, p and q for all points of the DEM, except boundary points [58, 150].

TABLE IX SUMMARIES OF THE MOST TERRAIN RESOLUTIONS AND FEATURES USED TO MODEL SOIL VARAIBLES

Authors	**Soil Variables**	**Terrain Features (Most Important Ones)**	**Resolution**
[153]	Soil drainage classes	Slope, slope-curvature ratio, elevation above local stream, slope gradient to local stream, distance to local stream, distance to local drainage way	30 m
[58]	A-horizon thickness, organic matter content, pH, extractable P, and silt and sand contents.		
[154]	A-horizon and carbonate depth	Slope gradient, curvature, drainage path, specific catchment area, elevation, wetness index, stream power, drainage proximity, accumulated flow	10 m
[58]	A-horizon depth, solum depth, E-horizon presence or absence	Plan curvature CTI	20 m
[155]	Profile Darkness Index (representing hydromorphic features)	Slope gradient, profile curvature, elevation above local depression	
[156]	Gilgai soil morphology. $CaCO_3$ enriched horizon depth	Slope gradient, aspect, mean-, horizontal-, and vertical curvatures. specific catchment area, CTI, SPI	11,8,5,4 m
[157]	Top soil clay	Elevation, slope, plan curvature, stream power index and wetness index	5 m
[66]	Soil profile depth, total phosphorus, total carbon	Slope, specific catchment area. CTI, flow direction, plus geology and climate data	25 m
[158]	Gravimetric water content at two depth, soil mineral N in the subsoil	Slope. profile curvature, plan curvature	5 m
[159]	Stratify geological areas	Elevation, depth, slope and upslope watershed areas	50 m
[160]	Soil types	Altitude, slope, aspect. Profile and plan curvature.	50 m
[161]	Presence of a non- calcareous clay-loam horizon	Slope gradient and slope aspect	20 m
[69]	Soil hydromorphy	Elevation above the stream bank, the slope gradient, the specific catchment area, and the compound topographic index	10, 20, 30, 50 m
[70, 72]	Soil types	PDD, slope, elevation	1 km
[162]	Soil Moisture	Slope, aspect, plan and profile curvature, and the secondary topographic attribute, the wetness index	5 m
[163]	Shallow landslide	Different slope	10, 25, 50 and 100 m
[164]	Soil depth	Slope (percentage and degrees); profile, plan, and mean curvatures; aspect; and the contributing area (accumulation area).	20 m

[165]	Soil types	Slope gradient, slope aspect, and various measures of slope curvature (total, profile, contour, and tangential).	5 – 30 m
[166]	Landscape characteristics	Slope and aspect than for curvature, topographic wetness index, and stream power index values.	10 – 30 m
[167]	Soil forming features, soil classes	terrain attributes	20 m

Using environmental correlation, different data analysis methods can be applied for spatial prediction. These include Bayesian rule-based systems [25]; neural nets, fuzzy logic [168]; generalized linear models [57, 59]; tree-based methods and co-kriging (e.g., [169]). Austin et al. [170] concluded that a combination of generalized linear models and generalized additive models was superior to tree-based procedures but all were acceptable for practical applications. Neural nets were unsatisfactory because of the difficulty of interpretation and requirement for specialised skills.

D. *What Is Wrong with Data-Driven Soil Mapping Models?*

The main limitation of the univariate geostatistical technique is the large amount of data that required to define the spatial autocorrelation. A problem with kriging is that the variance of the kriged estimates is less than that in the original data and this is referred to as smoothing.

Not only is the variance of the estimates reduced but also the sample variogram is altered so that the pattern of spatial variation is different from that of the original data. Consequently, kriged maps could never exist in reality (they could never be observed through measurement). This is a serious shortcoming since it means that kriged maps are unsuitable for input to simulation models [171] or cellular automata, and should not be used to build regression models which are then applied to measured values [172]. Conditional simulation or as it is also known, stochastic simulation or stochastic imaging [173], provides an alternative to kriging in which the variance and variogram of the original data are also honoured.

Thus, conditional simulation produces a map in which the general pattern of spatial variation in the original data is recreated, and which, consequently, is a “possible reality”.

The Data-Driven approach (e.g. OK) does not sufficiently utilize expert knowledge, as no attempt has been made in geostatistical approaches to directly integrate expert knowledge. OK does not exploit the relationship between environmental variables and soil properties. Also, the univariate usage of kriging is also limited in situations of complex terrain where the soil-forming processes are complex. The lack of adequate samples has been partially solved with increasing availability of ancillary information. There are economic and logistic reasons (more readily and cheaply available) for including the ancillary variables influencing soil variability.

OK has been modified in a variety of ways to better incorporate ancillary data and known soil–landscape relationships.

The use of remote sensing for mapping soil has been problematic because vegetation cover obscures much of the soil response making it necessary to search for indirect evidence that may be visible at the surface [174]. Thus, remote sensing cannot be applied alone to soil studies [175]. The use of proxies (such as topography, vegetation, drainage patterns) and field observations are important approaches for inferences about soil. In this connection, digital terrain models (DTMs) are used in a wide range of landscape investigations [145, 146, 176]. In this way, Dobos et al. [72] used satellite data complemented with DEM data; in order to correct the distortions caused by topographic variations of the landscape and provide additional data for soil–landscape modelling.

III. ON-THE-GO KNOWLEDGE-BASED AND DATA-DRIVEN METHODS FOR PSM AND PRECISION AGRICULTURE

Fig. 3 is combined with knowledge-based and data-driven methods to enable more precise statements on the status of the soil to be made. Because soil and the exogenous factors are multivariate, combinations of multivariate/univariate analysis using the CLORPT factors and the geostatistical methods are suggested. It is quite possible to combine information derived from DEMs and satellite observation with profile data and numerical models of soil processes. This technique has been proposed to produce rich, predictive models of the soil to meet predictive soil mapping requirements.

Data on soil formative environmental conditions (E) can be derived using GIS techniques, remote sensing and digital terrain model (Fig. 3). The variables used to characterize the soil-formative environmental conditions are decided based on the discussion between the person who conducts the knowledge acquisition (knowledge engineer) and the local soil expert(s). For a given area, the local soil expert would provide an initial list of environmental variables to be considered. This list is modified by the knowledge engineer based on the data availability and the importance of the variables impacting the pedogenesis in the study area. Because of the data availability and difference in pedogenesis over different areas, there is no fixed list of environmental variables to be included.

At the field scale, geostatistics have been successfully applied in such environments by using terrain attributes as ancillary data within many of the kriging routines described above. Such quantitative within-unit variability of soil properties is very useful in the field of precision agriculture and other situations (e.g., pollutants) where very detailed soil attribute information is needed at the field scale [44].

IV. SYNTHESIS AND IMPLICATIONS FOR FUTURE PSM AND PRECISION AGRICULTURE

The goal of this paper is to review and develop a method that can provide data for precision agriculture. Toward that end, the objectives of this article are as follows.

First is to collect the latest published information on mapping of soil properties in the context of precision

agriculture and determine the state of the art of this subject. Approaches to soil mapping can be divided into two main streams: knowledge-based, where the surveyor builds up a mental model of why each soil is where it is, and data-driven, where actual observations are observed and interpolated.

Second is to identify the limitations and gaps in the current mapping approaches. Conventional soil mapping has been criticized for being too qualitative. The conventional methods use expert knowledge of the surveyor. The surveyors act like a black box, because the users do not exactly know what parameters were considered and in what level, when the decision about the border line of the soil unit was made. It is unlikely to have two soil scientists whose soil maps of the same area would be identical. Quantitative models have been developed, which are being used to describe, classify and study the spatial distribution patterns of soil in a more objective way. These quantitative methods enable precise statements about the soil to be made. However, the new and emerging pedometric methods have also been criticized for being too expensive to adopt, as they require too many samples for them to be worthwhile, especially at the regional extent. This criticism is becoming untenable, especially with increasing availability of ancillary data, and the quantitative methods have proved to be equally efficient, if not better than, the conventional methods of soil inventory. Of course the best features of these two may be combined into a mixed approach.

Third is to suggest an accurate and inexpensive approach for soil mapping in the context of precision agriculture. Predictive soil mapping aims at spatial prediction of soil properties by combining soil observations at points with auxiliary information, such as contained in remote sensing images, digital elevation models and climatological records. As it was represented by the literature described in the current paper, digital data sources such as digital terrain data or satellite data are very promising tools for spatial soil characterization. Quantitative spatial soil models have got the advantage of quality assurance and paint a more realistic picture of the natural soil variation and uncertainty.

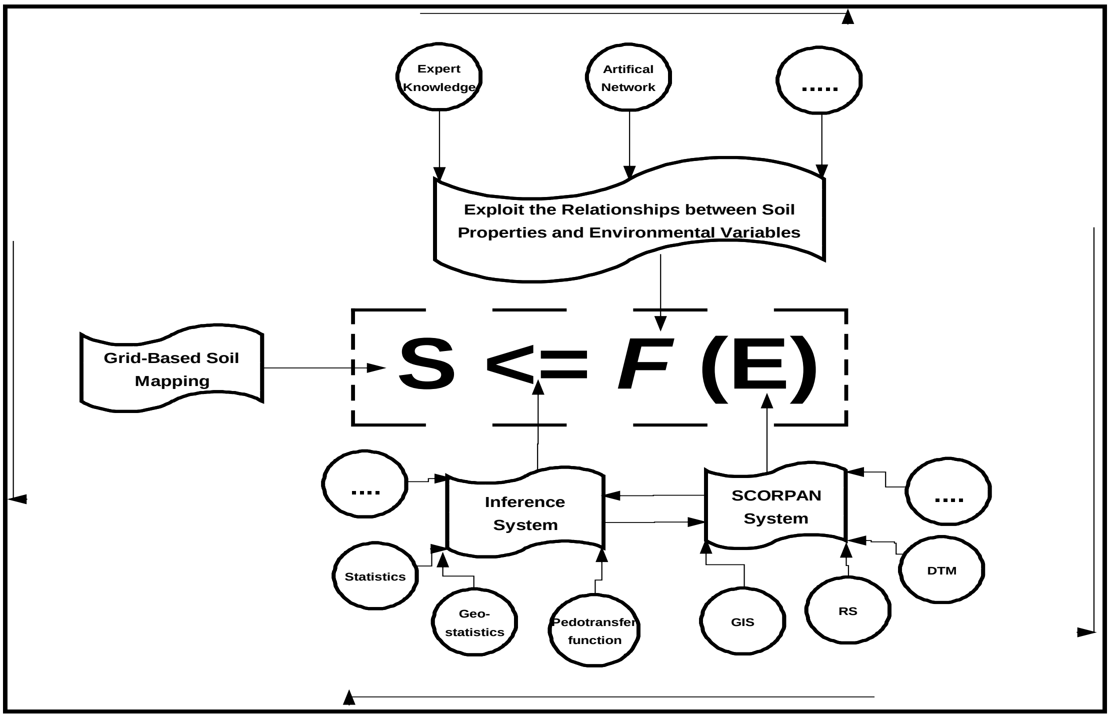

Fig. 3 Generic model combined of knowledge-based and data driven methods based on the concept that soil (S) is a function (f) of its formative environment (E)

Geostatistical tools have been successful at using terrain attributes and the spatial dependence of soil properties to interpolate between existing data points within individual fields. Statistical approaches provide a useful mean of predicting soil character. Terrain parameters and remote sensing images have played a key role in predictive soil mapping. Remote sensing images reflect surface roughness, color, moisture content and other surface characteristics of soils. When all is said and done, for us remote sensing is a useful tool in soil mapping, and not a soil-mapping method. Finally, proximal sensing offers the possibility of producing high resolution maps of soil properties. There is a variety of (in situ) soil-measuring systems. Developments in complimentary ground-based (e.g., electric conductivity, soil compaction, soil nitrate) sensors show promise to provide data sources to map spatial variability in soil properties. Electromagnetic induction (EM) provides another quantitative measurement for use in precision agriculture for mapping soil types and properties.

Although the purpose of this paper is to conduct and promote state-of-the-art soil resource inventory related to soil mapping and deliver usable knowledge to soil scientist and managers, it is believed that there are many fertile areas for future research. The success of precision agriculture depends strongly upon an efficient and accurate method for in-field soil property determination. This information is critical for farmers to calculate the proper amount of inputs for best crop performance and least environment

contamination. So, the question still to be answer is “Do users ignore soil map quality?”. This question can be used to build future research on soil map quality and accuracy. The aim is to improve the prediction accuracy of soil properties to enhance soil mapping process for precision agriculture.

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